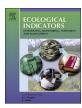
ELSEVIER

Contents lists available at ScienceDirect

# **Ecological Indicators**

journal homepage: www.elsevier.com/locate/ecolind



#### **Original Articles**

# Water use efficiency and TN/TP concentrations as indicators for watershed land-use management: A case study in Miyun District, north China



Guannan Cui<sup>a,b,d</sup>, Xuan Wang<sup>a,b,\*</sup>, Chunhui Li<sup>b</sup>, Yangyang Li<sup>a,b</sup>, Shengjun Yan<sup>a,b</sup>, Zhifeng Yang<sup>a,b,c</sup>

- <sup>a</sup> State Key Laboratory of Water Environment Simulation, Beijing Normal University, Beijing 100875, China
- b Key Laboratory for Water and Sediment Sciences of Ministry of Education, Beijing Normal University, Beijing 100875, China
- <sup>c</sup> Beijing Engineering Research Center for Watershed Environmental Restoration and Integrated Ecological Regulation, Beijing Normal University, Beijing 100875, China
- <sup>d</sup> Department of Environmental Science and Engineering, Beijing Technology and Business University, Beijing 100048, PR China

#### ARTICLE INFO

# Keywords: Land use planning Water use efficiency TN/TP pollution mitigation CLUE-S model MIKE-SHE model

#### ABSTRACT

Under dual influences of climate change and human disturbances, it is an important measure for sustainable watershed development to conduct land use planning with considerations of water saving and pollution control. In this research, the following tasks has been accomplished: (1) identifying runoff variations due to the land use changes, (2) investigating concentration variations in total nitrogen (TN) and total phosphorus (TP) in overland flow of different vegetation, (3) based on the rules found by the analyses above, determining the optimal land use demand of water, grass, forest, farm and construction lands through the adoption of multi-objective linear programming and a hydrological model (i.e., MIKE-SHE), (4) taking the relationship between land use changes and hydrological factors at the watershed scale as a corrected input of CLUE-S model to visually allocate land use under three scenarios (i.e., the most optimal situation, adjustment planning after the check point and the government planning for 2020), and further making the detailed crops distribution map for agricultural management with aim of improving water use efficiency and controlling TN/TP concentrations. Thus the "topdown" land use optimal allocation combining the macro scale and the field scale was implemented. The results can provide useful decision alternatives for the land use management of the watershed. Pine, chestnut and walnut were distributed on relatively steep hillside above 400 m. Crops like corn, millet and sweet potato were allocated to the flat areas with the slope less than 3° and the altitude below 400 m. The combination of CLUE-S model and MIKE-SHE model improved the accuracy of land use demand and specific vegetation distributions for farmers. The "top-down" land use optimal allocation considering both water saving and pollution control would support decision makers with feasible suggestions of optimizing land management at different scales.

#### 1. Introduction

Under the influence of climate change and human activities, water shortage has become a common problem in the middle of this century, which has seriously restricted the sustainable development of economy and society. China suffered from water shortage as well as the increasingly serious pollution coming with population, industrial and agricultural growth. Recent studies have shown that human activities on land use affected almost all of the nonpoint source pollution directly or indirectly (Xu et al., 2004; Chen and Fu, 2000). Not only the ecological environment, but economic and social development was suffered from water pollution to a certain extent (Li et al., 2003). Therefore, it is significant to promote the water saving and to coordinate the water conflicts in the river basin not only in favor of the unified water resource management, but also the construction of

water-saving society. To improve the water quality of river basin and guide the land use optimal allocation, it is significant to instruct land use spatial layout considering both ecological water saving and pollution control.

Optimization of land-use structure was aiming to find a way realizing economic, social and ecological benefits by future land use structure planning (Geng and Wang, 2000). Reasonable use of limited land resources could harmonize the contradiction among departments or industry land use options. To achieve the best economic, social and ecological benefits, it was important to make overall arrangement and reasonable layout through adjusting measures to local conditions for all kinds of land use types (Liu, 2003; Cai et al., 2011). With the maturity and improvement of GIS and other space technologies, spatial structure configuration model was extensively applied to land planning. More comprehensive and visual results were exhibited in the study that filled

<sup>\*</sup> Corresponding author at: State Key Laboratory of Water Environment Simulation, Beijing Normal University, Beijing, 100875, China. E-mail address: wangx@bnu.edu.cn (X. Wang).

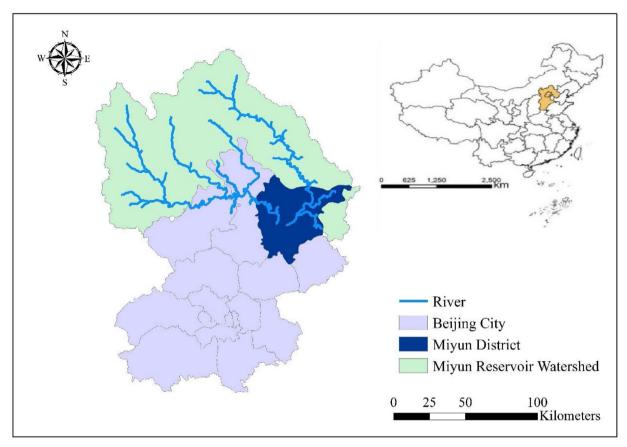


Fig. 1. Location of Miyun District, north China.

up the defects of quantitative structural configuration models. Quantitative structural configuration models had been gradually replaced by the following models: grey forecasting model and single objective linear programming model (Bryan et al., 2011); multi objective programming model (Osgathorpe et al., 2011); Markov chain model (Mitsova et al., 2011) and system dynamics model (Gastelum et al., 2010). Spatial structure configuration model had cellular automata model (Mitsova et al., 2011) and CLUE-S model (Verburg et al., 2002; Santini and Valentini, 2011). The combination of CLUE-S model and other models was a hotspot in the land use spatial structure. Due to the biding, the spatial configuration result error caused by the structure problem of the model itself can be reduced, thus improving the accuracy of land use spatial configuration. Hydrological models had been introduced into CLUE-S model for analysis of hydrological units (Zhang et al., 2014). SWAT model was widely applied together with CLUE-S model to consider the Non-Point Source pollution effects and achieved good practice effect (Zhang et al., 2011; Liu et al., 2014; Zhang et al., 2015). In summary, CLUE-S model could not only carry on the pretty good spatial disposition of land use but gain comprehensive research results by combination of other model simulations as well. However, there were lack of research bringing insight into quantitative relations between not only land use types changes and hydrological factors, but land use types changes and pollutant indicators by field monitoring and mechanism experiment. That led the land use allocation optimization to take actual situation into account less when the land use demand was decided. In order to get the land use allocation optimization plan considering both ecological water saving and pollution control, there was requirements for combining the field scale mechanism experiment or observation results. In addition, as for medium and small scale study area, more detailed information for crops pattern were also needed in the blue print of administrative planning. To give easy operation of the crop configuration in the field of farmland and forest planning could

facilitate the agricultural management department from the point of view of the overall optimization of the basin. These two aspects required further investigation in the land use configuration field.

Therefore, the objective of this research is to realize the land use optimal allocation of Miyun District by considering both water use efficiency and TN/TP concentrations. This objective entails the following tasks: (1) identifying runoff variations due to the associated land use changes, (2) investigating concentration variations in total nitrogen (TN) and total phosphorus (TP) in overland flow of different vegetation, (3) based on the rules found by the analyses above, determining the optimal land use demand of water, grass, forest, farm and construction lands through the adoption of multi-objective linear programming and a hydrological model (i.e., MIKE-SHE), (4) taking the relationship between land use changes and hydrological factors at the watershed scale as a corrected input of CLUE-S model to visually allocate land use under three scenarios (i.e., the most optimal situation, adjustment planning after the check point and the government planning for 2020), and further make the detailed crops distribution map for agricultural management with aim of improving water use efficiency and controlling TN/TP discharging. Economic benefit and ecological benefit were chosen as the main optimization goal. Optimal allocation of land resources was realized by the biding of multi objective linear programming model and CLUE-S model through providing explicit land use demand. According to the relationship between the land use changes and the hydrological factors on the field scale, that information was taken as corrected input of the land use model. The combination of CLUE-S model and MIKE-SHE model improved the accuracy of land use demand and specific vegetation distribution on the field scale. The "topdown" land use optimal allocation which combining the macro scale and the field scale would support decision makers with feasible suggestions of optimizing land management on different scales.

#### 2. Materials and methodology

#### 2.1. Overview of study area

Miyun District is situated in northeast Beijing City. Because of the only surface water source of drinking water (i.e., Miyun Reservoir) for the city located in this area, this district has an important strategic position in the maintenance of the water security for the capital. Since the past few decades, the annual runoff of the basin significantly reduced (Wu and Jiang, 2010; Li and Li, 2008). The geographic coordinates start from the west with longitude 116°39' 33" to east with longitude 117°30′ 25". It crosses 69 km from west to east. The district covers from the south with the latitude 40°13′7" to north with the latitude 40°47′ 57". It lies between the Yanshan mountain and the North China Plain. There are mountains around on the east, north and west, and Miyun Reservoir is located in the middle. The Miyun District is in a warm temperate zone with semi-humid continental monsoon climate. Its main land use types were farm, forest, grass, water area and construction land. The annual average temperature is 10.8 °C. It has an area of 2227 square kilometers and a population of 460,800. The district is divided into 2 streets, 17 towns, and 1 ethnic rural township (Fig. 1).

There are more than four reservoirs in Miyun area. Miyun reservoir is the most important drinking water source in Beijing City, the capital of China. It locates at latitude of 40°-42°, longitude 116°-118°. On the north of the basin is the Inner Mongolia Plateau while Yanshan Mountains across the basin on the south. Watershed area covers approximately 4854 km<sup>2</sup> and witnesses 2059 m elevation change. Mountain body is mainly composed of granite, gneiss, sandy conglomerate and limestone and suffers serious rock weathering. Brown soil and cinnamon soil are the main types. Upstream has a thick loess cover and is in a situation of soil erosion because of the mixed composition with rocks. The climate is continental monsoon climate with average annual rainfall of about 494 mm. There are rich resources of vegetation containing mixed coniferous as the dominant species, grass covers more than 40% of the domain. The Miyun reservoir provides  $7.0 \times 10^9 \,\mathrm{m}^3$  of drinking water each year to Beijing City approximately. This amount counted 50% of surface water supply in the city and 60% of the urban water works. Under the big goal of sustainable development for the whole watershed, studies on runoff responses of land use change are very important for water provision security and adaptive strategies making.

Due to the drought and water use increase of upstream region in recent years, the annual runoff of the basin significantly reduced in the wake of water conservancy project construction, water diversion project or water and soil conservation (Wu and Jiang, 2010; Zheng et al., 2016; Ou et al., 2016). Such human activities multiplied also led to water quality deterioration and intensifying eutrophication risk. The twin tributaries, i.e. Chaohe River and Baihe River, have witnessed clear runoff reduction on the impacts of human activities and climate change (Zhong et al., 2013). In addition, studies have shown that the nutrient level of the water body in Miyun reservoir had been in a trend of eutrophication (Jiao et al., 2015; Xu et al., 2016). TN and TP exceeded China National Standard II for surface water 5.08 times and 1 time respectively (Li et al., 2016). The situation was severe for drinking water source. Prevention of non-point source pollution and improvement of water use efficiency of the river basin were the main purposes. Under the impact of precipitation, the runoff and water quality variations due to different land use types were monitored. All the quantitative disciplines required above were solid base for constructing the theory frame of the land use optimization considering both ecological water saving and pollution control. Being verified and popularized in practice, the theoretical foundation could support integrated management of the river basin for the decision makers and be very important meanings for the source of drinking water in Beijing City.

#### 2.2. Data acquisition

This study established the data base of the study area mainly through field reconnaissance, site collection, field experiments and literature review. Data base included the following: (1) Digital elevation model with the scale of 1:1000000 from Beijing Zhentu Information Co. Ltd; (2) Land use map of 1:1000000 scale from Chinese Academy of Sciences Institute of Geography; (3) Soil map of 1:1000000 scale from Chinese Academy of Sciences Institute of Soil Science; (4) Meteorological data from local weather stations, with collection frequency being once every half hour; (5) Hydrological data from automatic water level monitor set on the outlet of the watershed. The water depth data was selected from June to September in 2014 and 2015. According to the water level-discharge curve, the flow of the outlet of the basin was found; (6) Water quality data: TN, TP of the overland flow and outlet flow; (7) Soil properties: soil moisture content of each 10 cm soil layers (from the surface to 40 cm) by soil moisture meter, TN and TP concentrations of the medium and bottom layers (20 cm and 40 cm); (8) Vegetation attributes: photosynthetic and transpiration characteristics of vegetation by LCI portable photosynthetic apparatus. Monitoring time from 8:00 to 14:00 according to the growing period.

To examine the water quality, TN and TP were surveyed in the soil and water samples of each sample point (Table 1). These observation results can provide significant references for multi-objective linear programming to calculate the optimal land use demand considering both ecological water saving and pollution control in the research. The data related to precipitation, evapo-transpiration, runoff, and TN and TP concentrations were collected from June to September in 2014 and 2015. The soil samples were collected from the depth of 20 cm and 40 cm in the soil profiles. TN was TP concentrations were measured by Kjeldahl Determination (HJ 717-2014) and Mo – Sb Antispetrophotography Method (NY/T 88-1988). As to the water samples, cofferdams were built of 20 m\*25 m for overland flow influx. The data set was collected after precipitation events. The main land use types in Miyun District were farm, forest, grass, water area and construction land.

### 2.3. Methodology

This research combined the MIKE-SHE Model and CLUE-S Model to conduct the optimal land use planning of Miyun District. With spatial data and attribute data collected from literatures, monitoring departments and field investigations on the study site, the hydrological model was utilized for investigating the impacts of different land use types on runoff after model calibration and validation. Multiple linear regression method was used for revealing quantitative relations between land use changes and hydrological factors. TN and TP concentrations were also revealed in the overland flow generated by different land use types. The second phase applied to discover the quantitative impacts of distinguish land use types on runoff and TN, TP concentrations which provide evidence for seeking the most optimal land demand. On the basis of the shakedown test of the land use model, CLUE-S Model were ensured the suitability for the study area. Multi-objective program supported the

Table 1
Location and slope of sample points.

Sample code	Land use	Latitude	Longitude	Slope
1	Pine	N40°28′34″	E117°8′25″	35°
2	Chinese chestnut 1	N40°28′46"	E117°8′34"	35°
3	Chinese chestnut 2	N40°28′41"	E117°8′39"	$10^{\circ}$
4	Walnut 1	N40°28′41"	E117°8′14"	$20^{\circ}$
5	Walnut 2	N40°28′42"	E117°8′39"	3°
6	Millet	N40°28′43"	E117°8′41"	3°
7	Corn	N40°28′35"	E117°8′25"	5°
8	Sweet potato	N40°28′36″	E117°8′27″	3°

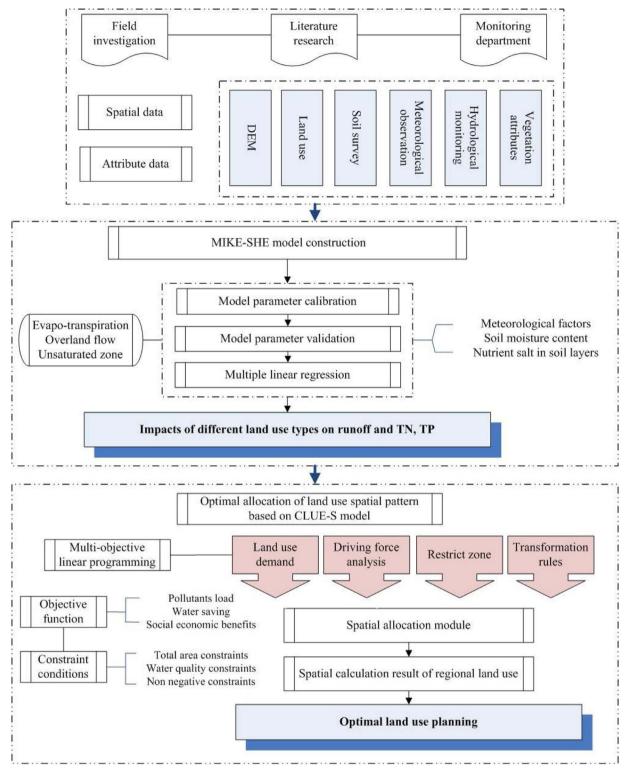


Fig. 2. The technology roadmap of the research.

land use model with more accurate land use demand by considering the pollution loads and ecological water saving to achieve economic, ecological and environmental goals for the study area. The most optimal land allocation results were finally spatialized by the land use model. Comprehensive land use optimal distribution improved the scientific and effective administrative management of Miyun District. The technology roadmap of the research is shown in Fig. 2.

## $2.3.1. \ \textit{MIKE-SHE} \ \textit{model} \ \textit{building} \ \textit{for} \ \textit{Miyun} \ \textit{District}$

Since the mid-1980's, MIKE SHE model has been further developed and extended by DHI Water & Environment. As a flexible framework for hydrologic modeling, MIKE SHE model covers the major processes in the hydrologic cycle and includes process models for evapo-transpiration, overland flow, unsaturated flow, groundwater flow, and channel flow and their interactions. This research used the water movement (WM) module for the simulation. It consisted of many sub-modules: evapotranspiration (ET), soil water movement (SWM), overland flow

Table 2
Parameters considered in the MIKE-SHE model.

MIKE-SHE modules	Principle calibration parameters	Other parameters
Overland flow (sub-catchment based)	Surface roughness	Detention storage Slope parameters
River flow	River bed roughness River bed leakage coefficient	
Actual evapo- transpiration Unsaturated flow (finite difference)	Leaf area index Root depth Saturated hydraulic conductivity	Canopy interception FAO crop coefficient Soil water contents at saturation, field capacity, and wilting point Soil pedo-transfer function parameters

(OF), channel flow (CF) and unsaturated zone (UZ). The parameters required in the model were shown in Table 2.

The simulation period was the flood season (May to September) in 2014. Correlation coefficient ( $R^2$ ) and Nash-Suttcliffe coefficient (NS) were chosen for evaluating the performance of the model (Nash and Sutcliffe, 1970). Correlation coefficient  $R^2$  was used for anastomosis degree analysis between measured values and simulation values. The lower  $R^2$  was the worse anastomosis degree the model represented. Uncertainty factor NS was a comprehensive factor which could quantitatively characterize the anastomosis extent of the whole hydrological process. The larger NS represented the higher simulation efficiency the model illustrated.

$$NS = 1 - \frac{\sum_{i=1}^{n} (Q_m - Q_p)^2}{\sum_{i=1}^{n} (Q_m - Q_{avg})^2}$$
(1)

where  $Q_m$  is measured value;  $Q_p$  is simulation value;  $Q_{avg}$  is average measured value; n is number of observations.  $R^2$  and NS were widely utilized to evaluate the simulation efficiency. It was a better result when NS > 0.75, it was satisfied when NS was in the interval of 0.36–0.75. The result was satisfied when  $R^2$  > 0.60 while NS > 0.50 (Moriasi et al., 2007).

#### 2.3.2. The CLUE-S model building for Miyun District

Land use was the interaction result of the social economy and natural environment, thus this research considered the driving factors comprehensively. The factors included the three following compositions and were displayed in Figs. 3–5.

- (1) Topographical factors: DEM, slope and aspect of Miyun District;
- (2) Accessibility factors: the distance to the railways, national roads and secondary roads in Miyun District;
- (3) Social and economic factors: GDP and population density of Miyun District.

In the model we have assigned each land use type a dimensionless factor that represents the relative elasticity to conversion, ranging from 0 (easy conversion) to 1 (irreversible change). The user should specify this factor based on expert knowledge or observed behavior in the recent past. Water and construction land are the most different conversion types. Forest ranks the following, while grass and farm land can transfer relatively easy. As a result, the elastic coefficient of different land use types was defined as water body and construction land with 0.9, forest land with 0.8 and grass and farm land with 0.6.

After the simulation of model, the Kappa coefficient calculated by Eqs. (2)–(5) was chosen to evaluate if the driving factors could explain the land use changes and the model was suitable or not for the future

land use pattern forecast.

$$Kappa = (P_o - P_c)/(P_p - P_c)$$
 (2)

$$P_{o} = P_{11} + P_{22} + P_{33} + ... + P_{ij}$$
(3)

$$P_{c} = R_{1} * S_{1} + R_{2} * S_{2} + R_{3} * S_{3} + \dots + R_{i} * S_{i}$$
(4)

$$P_p = R_1 + R_2 + R_3 + ...R_i (5)$$

where  $P_o$  is the correct observed value after comparing the real map and simulation diagram;  $P_c$  is the expected value of the accidental correct conditions on the simulation diagram;  $P_p$  is the correct real value on the real map; j is the land use type. The Kappa index would be 1 if the simulation diagram is exactly the same as the real map. When Kappa  $\geq 0.75$ , there is good consistency between the two; when  $0.4 \leq \text{Kappa} < 0.75$ , the consistency is in general; when Kappa < 0.4, the result reveals poor consistency.

For administrative departments under the district level, the more explicit land use patterns were needed for farmer scale. To get the planting instruction, the habitual nature of the plants was taken into consideration. Combined the CLUE-S driving factors analysis and the existing conditions, the selected species could be put on the most suitable place. The DEM, slope and aspect were chosen for the factor list to evaluate the suitability of the land. Except the factors mentioned above, precipitation and temperature were also important for the vegetation cultivation. As a result, these five factors were finally decided. Each factor would be divided into different levels by the reclassification tool in GIS. The reclassified raster data of each factor were added together to gather the whole impacts by the raster calculator.

#### 2.3.3. Multi-objective program for land use demand

In order to realize the economic benefit, social benefit and ecological benefit of the whole district, multi-objective linear programming model was selected to optimize the quantity structure in the region

Social and economic goals:

$$\operatorname{Max} F(\mathbf{x}) = \sum_{i=1}^{5} a_i x_i \tag{6}$$

where F (x) is the objective function of economic benefit;  $a_i$  (i = 1,2,... 5) represents the price index for the unit production.

Environmental goals:

$$\operatorname{Min} \operatorname{TN}(\mathbf{x}) = \sum_{i=1}^{5} n_i x_i \tag{7}$$

$$\operatorname{Min} \operatorname{TP}(\mathbf{x}) = \sum_{i=1}^{5} p_i x_i \tag{8}$$

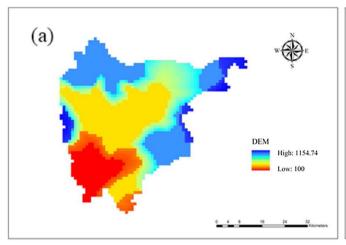
where TN (x) is for the total nitrogen content of the overland flow;  $n_i$  (i = 1, 2,... 5) represents the partial correlation coefficient of the effect of land use on the total nitrogen; TP (x) is for the total phosphorus content of the overland flow;  $p_i$  (i = 1, 2, ...5) represents the partial correlation coefficient of the effect of land use on the total phosphorus.

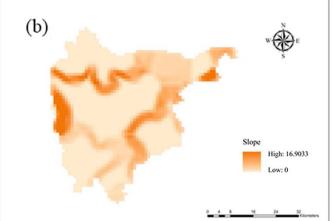
Ecological goals:

$$\operatorname{Max} R(x) = \sum_{i=1}^{5} r_{i} x_{i}$$
(9)

Min E(x) = 
$$\sum_{i=1}^{5} e_i x_i$$
 (10)

where R(x) is for the discharge of the watershed;  $r_i$  (i = 1, 2,... 5) is the partial correlation coefficient of the flow rate corresponding to the land use types; E(x) is for the evapo-transpiration of the basin;  $e_i$  (i = 1, 2,...





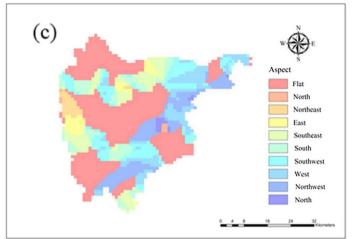


Fig. 3. Topographical factors (a) DEM, (b) slope, and (c) aspect in Miyun District.

5) represents the partial correlation coefficient of the land use effect on evapo-transpiration;  $x_i$  indicates land use types ( $x_1$  for water body;  $x_2$  for grass land;  $x_3$  for forest land;  $x_4$  for farm land and  $x_5$  for construction land).

The constrain conditions were as follows: The area of the five types of land use should be the total area of the Miyun Reservoir upstream basin area in Miyun District.

$$\sum_{1}^{5} x_{i} = 210800 \text{ ha}$$
 (11)

Water environment quality should at least reach III class water quality standards.

$$TN(x) \le 1.0 \text{ mg/L} \tag{12}$$

$$TP(x) \le 0.2 \, mg/L \tag{13}$$

The value of all kinds of non-negative constraints should be in line with the practical significance. The land use type area should be positive.

$$X_i > 0, i = 1, 2, 3, 4, 5$$
 (14)

The optimal land use demand could be solved through the above objectives and constraints. The calculation process was conducted by Lingo. The results were input into the CLUE-S model and illustrated visually in GIS.

#### 3. Results and discussion

#### 3.1. Land use impact on water and nutrient salt contents

#### 3.1.1. Precipitation and evapo-transpiration characteristics

Fig. 6 illustrates the precipitation trends. The total precipitation in 2014 was 420.8 mm, and it was slightly different in 2015 (410.5 mm). These two years' annual precipitations were less than the average (660 mm) which were normal flow years. The peak (54 mm) occurred in July of 2014 and shifted to August in 2015. There were plentiful precipitation in June and August in 2014. In contrast, the watershed was well watered in August in 2015.

The evapo-transpiration amount for each day is shown in Fig. 7. The total amount was 2557.814 mm and 2521.476 mm in the year 2014 and 2015 respectively. The year 2014 exceeded the year 2015 nearly 40 mm as a whole. The difference began from June and lasted for the four months. Compared to the precipitation, the evapo-transpiration far outweighed which led to the result that there was surface flow only when the precipitation events occurred.

Precipitation and evapo-transpiration data of the year 2014 and 2015 were collected. The water use efficiency (WUE) depended on plant photosynthesis and transpiration. The equation was as follows:

$$WUE = Pn/Tr$$
 (15)

where WUE is water use efficiency; Pn is photosynthetic amount; Tr is evapo-transpiration amount. As the pine needles could not meet the requirement of the leaf chamber so that the measurement of pine trees were not able to be realized by the instrument. Pine trees' (*Pinus tabulaeformis*) WUE was referenced from Hao's research (2016).

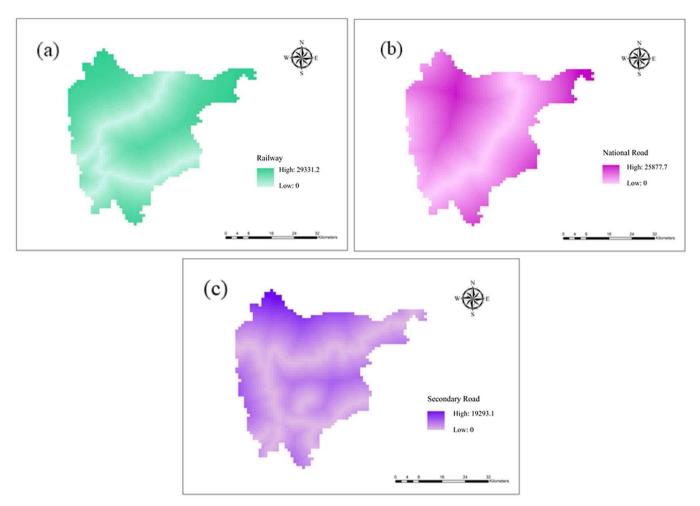


Fig. 4. Accessibility factors (a) the distance to railways, (b) the distance to national roads, and (c) the distance to secondary roads in Miyun District.

Table 3 demonstrated the WUE of different vegetation. Pine trees' WUE was less than 3.50 and went up in September which meant they had better water use performance in relatively dry season. Chinese chestnut had the most efficient water use in August and reduced as the time went on. While walnut had the exact opposite trend that August experienced the minimum value and reached the peak in September. The economic forest had better WUE about 8–10. Compared with above, the farm plants expressed worse especially sweet potato. The WUE curve of sweet potato was smooth and under the value of 1.5

through the three months. Millet and corn had the maximum value in July and decreased afterwards.

3.1.2. TN, TP distribution characteristics in soil layers and overland flow
Based on the hydrological year division of the drainage area, TN and
TP loads had different characteristics in high flow year or low flow
year. Previous research showed that typical high flow year experienced
955.46 t of TN loads and 47.78 t of TP loads. While in low flow year,
total TN and TP loads were 256.42 t and 9.39 t respectively (Geng et al.,

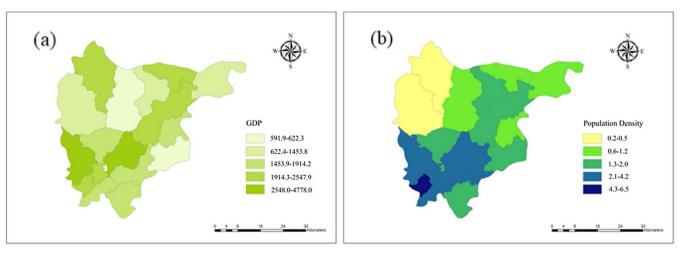


Fig. 5. Social and economic factors (a) GDP and (b) population density in Miyun District.

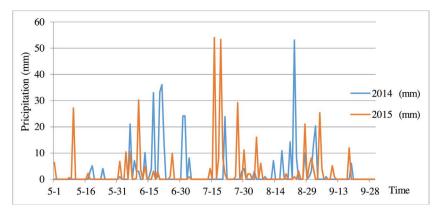


Fig. 6. The precipitation in the year of 2014 and 2015.

2016). Water yield impacted the pollution in an obvious way so that it was significant to balance the relationship between water resource and pollution control. Figs. 8 and 9 illustrated the TN and TP content in overland flow collected from the sample points of different vegetation. TN and TP concentration had the same trend as that of the separate vegetation species and were lower the greatest value of the overland flow. TP concentration of the outlet was mostly under the II level and of the standards and fluctuated to the III level in September (National water quality standards). TN exceeded the V grade that signified serious fresh water condition. The nitrogen source in the watershed had become the main factor of the basin pollution. When there was a precipitation event, a large amount of nitrogen and phosphorus elements were dissolved in the runoff while the soil was in the process of erosion, transportation and accumulation. The larger the rainfall intensity was, the more pollutants tested in the water body. Light rain led to lower kinetic energy and rainfall erosion capacity after reaching the surface through the canopy and litter layer. The milder the soil erosion was, the smaller the average concentration of pollutants was.

As to the TN concentration, the flow scoured over pine trees had the strongest Nitrogen collection capacity. The other types of plants were in the same group that differed not so much on pollutant concentration. However, the curve of the Chinese chestnut sample 1 suddenly rose high to 13.5 of observation on  $22^{\rm nd}$  August. Except pine trees, all the curves including the outlet line had the bump on the same day. There was the most intense rainfall at that moment, so the extreme value appeared.

As to TP concentration, the outlet value was the lowest among all the observation values. The pine trees, Chinese chestnut 2 and walnut 2 had smooth trend until the curve rose sharply at the end of the monitoring period. The forest representatives performed more sensitive with the huge precipitation. Contrary to species above, plants on farm land had good control for preventing the phosphorus loss. This result was not the same as the general researches on account of the terrace

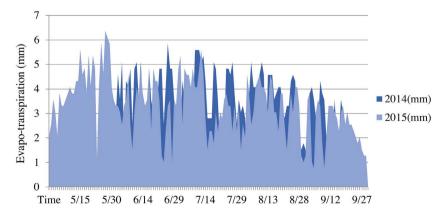
Table 3
The WUE of different vegetation.

	July	August	September
Pine	3.35	3.49	3.78
Chinese chestnut1	4.74	7.70	0.62
Chinese chestnut2	4.95	4.94	1.00
Walnut1	3.27	0.57	5.71
Walnut2	2.62	0.25	10.60
Sweet potato	0.93	0.78	1.20
Millet	4.29	2.73	1.57
Corn	4.64	1.51	3.06

Note: the WUE of Pine is from Hao, 2016.

like pattern of farm land. At the end of the flood season, the crops were in the period of maturity. The nitrogen and phosphorus concentration in the soil were absorbed by the plants and led to a result of smaller value occurrence.

TN and TP concentrations were corresponding to those in water samples. Rainfall washed off the nitrogen and phosphorus matters from the soil surface to the overland flow. Fig. 10 revealed TN and TP concentrations in soil profiles of different land use types. In general, TN concentrations showed less diversely with the soil went deeper and all kinds of vegetation gathered in TN characteristics. Because of the water wash, the soil contained a small quantity of Nitrogen between the amount of 0.05–0.1 mg/L. Like the TN trend, TP concentrations also went down from 20 cm to 40 cm in soil profiles. However, different land use types were easily distinguished and had stronger phosphorus fixation ability. Soil of Chinese chestnut sample point 2 had the peak value of nearly 0.25 mg/L on the surface. Surface soil was more likely influenced by human agricultural activities than the deeper layers. But the soil was barren and the deepest depth was around 50 cm to the end. That made the significances were not so obvious.



 $\textbf{Fig. 7.} \ \, \textbf{The evapo-transpiration in the year of 2014 and 2015}.$ 

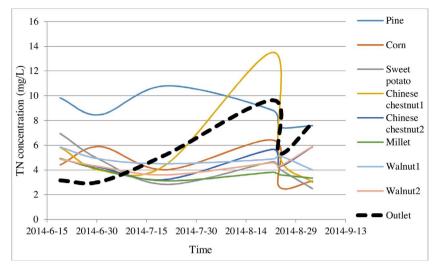


Fig. 8. TN concentration in overland flow collected from the sample points of different vegetation.

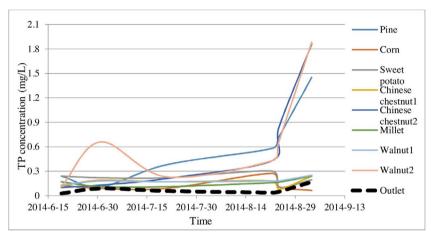


Fig. 9. TP concentration in overland flow collected from the sample points of different vegetation.

From the experiment results above, the watershed faced severe pollution problem. Slope was an important factor to affect the N/P element loss process. Therefore, terrace engineering was an effective kind of soil and water conservation slope treatment project, as it could increase the soil moisture and nutrients as well as retain the natural precipitation and sediment in the upper part. Besides the project means, source control was the foundation to prevent the expansion of the pollution issues. Reducing the use of fertilizer and pesticide could be realized by soil testing and fertilizer recommendation or optimal integration of microbial, biological and chemical systems.

#### 3.1.3. Land use changes impact on runoff

Through multiple calibration, R<sup>2</sup> of daily runoff simulation value and measured value was 0.92 while NS was 0.79. This meant the model had good fitting effect which could be applied in the hydrological process simulation. Fig. 11 showed the discharge observation and simulation calibration results of flow curves appearing on 6/05, 6/16, 6/19, 6/30, 7/20, 8/22 and 8/31 after precipitation events in 2014.

The hydrological data of the same period (May to September) of 2015 was adopted in the validation process.  $R^2$  of daily runoff simulation value and measured value was 0.89 while NS was 0.75.

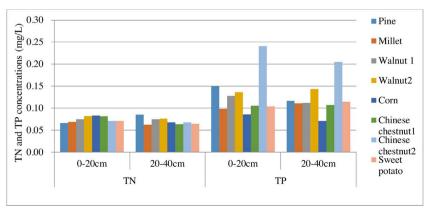


Fig. 10. TN and TP concentrations in soil profiles of different vegetation.

Ecological Indicators 92 (2018) 239-253

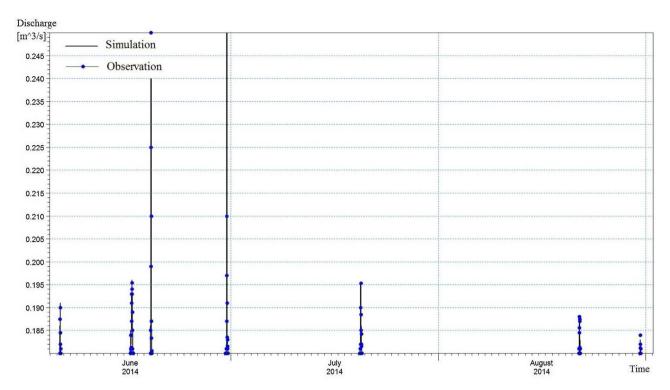
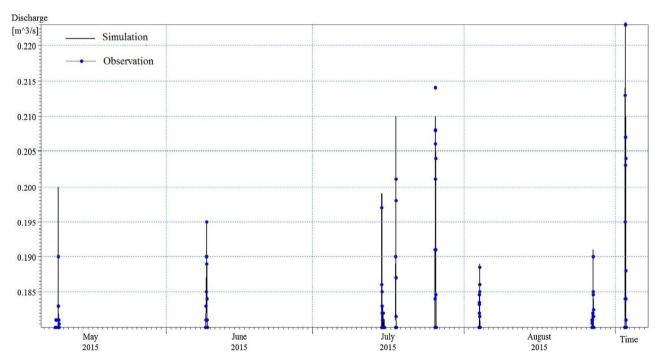


Fig. 11. The model calibration of observation values and simulation values in 2014.



 $\textbf{Fig. 12.} \ \ \textbf{The model validation of observation values and simulation values in 2015.}$ 

The model had good fitting effect which could be applied in the hydrological process simulation. Fig. 12 showed the discharge observation and simulation validation results of flow curves appearing on 5/09, 6/09, 7/15, 7/18, 7/26, 8/04, 8/27 and 9/03 after precipitation events in 2015.

The results shown in Table 4 revealed that the forest and grass land types influenced the total runoff the most. If there were significant increase of total runoff, that could be mainly attributed to the rise of the forest and grassland area. Construction land increase clearly could lead to the reduction of the total runoff. The impact trends performed

**Table 4**Partial correlation coefficient of LUCC and hydrological factors.

	Forest	Farm	Grass	Construction	R
Total runoff Overland flow Base flow Infiltration Transpiration	0.724 - 0.629 0.499 0.482	0.32 -0.279 0.443 0.473	0.832 - 0.388 0.255 - 0.321	-0.304 0.927 -0.476	0.895 0.938 0.712 0.703 0.705

Table 5
The land use changes from 2000 to 2005.

Land use type	2000		2005	Change amount		
	Area(ha)	Percentage (%)	Area(ha)	Percentage (%)	(%)	
Water	18700	8.87	18300	8.68	-0.19	
Grass	28400	13.47	29200	13.85	0.38	
Forest	110900	52.61	110400	52.37	-0.24	
Farm	44600	21.16	43600	20.68	-0.47	
Construction	8200	3.89	9300	4.41	0.52	

opposite in the overland flow conditions. Forest, farm and grass had negative influences on overland flow but helped to give the total runoff a rise because they promoted the supply of underground runoff. These three kinds of vegetation would be positive correlation with base flow and infiltration, while control the transpiration amount. Construction land provided overland flow easily but presented negative correlation with infiltration owing to the impermeability. The regression analysis could offer theoretical support for optimization of the land use planning. Water conservation could be realized by optimal land use allocation. At the same time, some project ways were also helpful to make it convenient while conducting proper land use planning. Farm land was suitable for terrace project according to the topographical situation. It would intensify the rainfall infiltration on the spot, and keep the soil water storage year by year.

#### 3.2. Land use allocation scenarios with CLUE-S model for Miyun district

#### 3.2.1. The development of the model

Table 5 shows the land use changes from 2000 to 2005. During these 5 years, the construction land increased with the most area percentage (0.52%) due to economic development. Grass land also had a growth trend while the other three land use types declined. Water body reduced 0.19%. However, this downsizing situation should be prevented. Farm land shrunk 0.47% from the original, nearly as twice as the forest. The land use area conditions in 2005 were the objective demand in the CLUE-S simulation based on the data in 2000.

We used SPSS to perform the statistical analysis. It was necessary to perform a logistic regression analysis to test the hypotheses specified for the different land use types. Output would be generated in a special window which showed the variables in the equations and ROC curves. ROC is standing for Receiver Operating Characteristic Curve, also known as Sensitivity Curve. The ROC characteristic is a measure for the goodness of fit of a logistic regression model similar to the R<sup>2</sup> statistic in Ordinary Least Square regression (Pontius and Schneider, 2001). A completely random model gives a ROC value of 0.5; a perfect fit results in a ROC value of 1.0. Fig. 13 showed the ROC curves for explaining the driving factors of different land use regression equations.

The exe(B) gained by SPSS analysis in Table 6 was occurrence rate of events. Incidence rate was an important indicator to measure the influence degree of explanatory variables on the dependent variables. When  $\exp(B) < 1$ , the incidence rate reduced; when  $\exp(B) = 1$ , the incidence rate stayed the same; when  $\exp(B) > 1$ , the incidence rate increased. If  $\exp(B)$  was in the interval from 0.98 to 1.02, the change was not apparent. On the basis of Tables 4–6, population density had remarkable impact. The influence degree ranked as farm > grass > forest > water. Only the incidence rate of farm increased. Slope effected farm and forest in opposite ways. Farm land was affected more easily. The other driving factors' impact kept stable on the land use changes.

According to the ROC results, the selected driving factors could explain the distribution of land use pattern. The ROC of water and construction land were bigger than 0.8 which illustrated better explanatory ability of the driving factors. In contrast to the two land

use types above, forest and grass land were not so suitable for the chosen driving factors (ROC were less than 0.7). Farm land was in the medium level. The factors were more fit for the land use types which were affected by people. It was relatively difficult to describe the distribution of the natural environment.

The result of the model could be imported into ArcGIS to be visualized. Fig. 14 demonstrates the actual and simulation map of the year 2005. Kappa index calculated by using Eq. (2) and used to evaluate the classification accuracy of remote sensing image and also to compare the consistency of two maps. After the calculation in SPSS, the Kappa index of the 2005 land use simulation was 0.91. The model successfully forecasted the pattern of the year 2005 based on the given data of 2000 and eight driving factors. This model could be applied for the future prediction.

#### 3.2.2. Optimal allocation of land use types based on scenarios

The optimal land use demand for each type was calculated by multiobjective linear programming which was demonstrated in Table 7. The water area reduced from the year 2000–2005. To prevent this trend, the calculation was deducted on the base of the unchanged water body area. Forest had planned an increase for the reason that it could help the runoff raise. Grass and farm land areas dropped for that construction land had growth for the economic development. The construction programs almost were built near the downtown of Miyun District because the convenient traffic conditions and financial base.

The expectation was set but the reality did not perfectly follow the planning. To ensure the blueprint could be better executed, the check time point was found during the whole planning era. According to the land use report in the year 2010, the areas occupied did not fit to the optimized calculation results. As to the water body, it decreased more than 5000 ha for the huge raise of construction exploration. The patches of water area were replayed by new types of vegetation. Compared the differences, new plan should be formulated in the future 5-10 years. Based on the principle of water conservation and controlling the construction expansion, later panning of land use demand were recounted. Forest and farm lands were adjusted to the optimal result of the land use planning. Grass land was sacrificed for the two land use types above for guaranteeing the runoff amount and pollutants controlling. Table 7 illustrated the detailed land demand information of the year 2000 and 2005, as well as the three scenarios (i.e., the most optimal situation, adjustment planning after the check point and the government planning for 2020).

The particular crop allocation results were visualized in Figs. 15. All the vegetation was distributed according to the best growth condition. Forest could be divided in to natural forest and economic forest. As for natural forest, pine trees are dominant species. Economic forest has two representatives like chestnut and walnut. Pine tree was the main species of natural forests in Miyun district which was located on the mountainous area in the shade above 400m. Chestnut was a species that was suitable for the wide range of climatic and soil conditions. The best average temperature for the chestnut growth was 8–15  $^{\circ}$ C. Chestnut was adapting to the rainy and humid climate with the precipitation rate from 600 mm to 700 mm. Chestnut was also fond of light because sufficient illumination could help the tree crown growth and fruit formation. The chestnut trees were normally distributed in the mountainous area and sloping fields, and they were not restricted to the slope conditions. So the sunny hill side or open valley with slope bigger than 5° were chosen. Similar with chestnut, the other type of economic forest walnut needed plot with adequate sunshine. The annual average temperature required above 9-16 °C and the annual average precipitation needed to be greater than 800 mm. For the altitude, the walnut trees were generally cultivated in the area of more than 1000 m above sea level. As for Miyun District the altitude requirement was hard to meet. As a result, the walnut had the priority to lay on high altitude area in the region.

Corn, millet and sweet potato were on the behalf of farm land

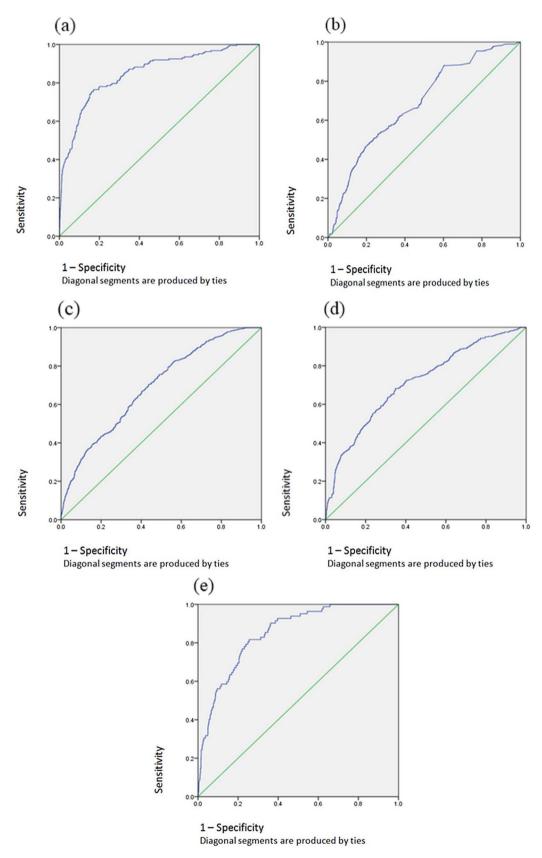
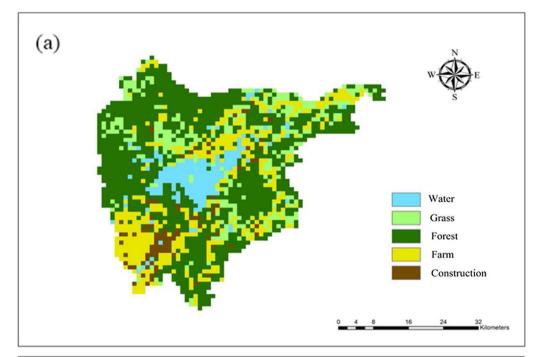


Fig. 13. ROC curves of a logistic regression between driving factors and (a) water, (b) grass, (c) forest, (d) farm, and (e) construction land use changes, respectively.

Table 6
Beta values and exponent beta values of logistic regression for different land use types.

G. Cui et al.

Driving factors	Water B	exe(B)	Grass B	exe(B)	Forest B	exe(B)	Farm B	exe(B)	Construction B	exe(B)
Miyun DEM	-0.01012	0.98993			0.00159	1.00159	-0.00115	0.99885	-0.00714	0.99288
Aspect	-0.00908	0.99096	0.00459	1.00460	0.00128	1.00128				
Slope					0.07256	1.07526	-0.14113	0.86838		
Distance to railway		4							-0.00016	0.99984
Distance to national road									-0.00016	0.99984
Distance to secondary road	0.00010	1.00010			0.00009	1.00009	-0.00007	0.99993		
GDP	-0.00048	0.99952								
Population density	-0.23435	0.79109	-0.54541	0.57960	-0.32624	0.72163	0.44118	1.55454		
ROC	0.851		0.683		0.693		0.713		0.850	



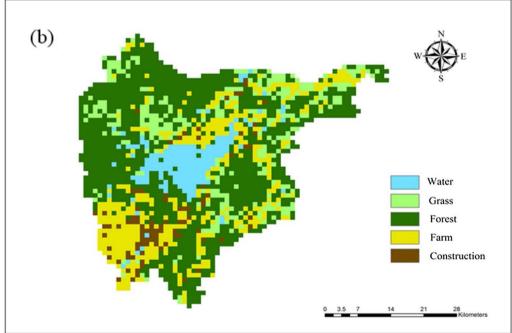


Fig. 14. The actual (a) and simulated (b) land use of Miyun District in 2005.

Table 7
Land use allocation of Miyun District (ha).

	Water	Grass	Forest	Farm	Construction
2000	18700	28400	110900	44600	8200
2005	18300	29200	110400	43600	9300
Optimization	18300	18800	135580	21286	16834
Check time point	13050	26004	131341	17521	22884
Adjustment planning	13050	18000	135666	21200	22884
Government planning for 2020	13026	18457	132917	21200	25200

vegetation. These crops were allocated on the flat areas with the slope less than 3° and the altitude below 400 m. Corn was the most widely cultivated crop in the district. The optimum temperature was 18–28 °C and it varies according to different periods. Intense light was necessary for increasing net photosynthetic rate. Millet was widely planted in the north part of China. It was a warm crop which needs temperature guarantee range of 15–25 °C and maximum tolerated temperature is 30 °C. Millet developed better in short day light. Shortening of sunshine promotes earlier head sprouting and better development. Sweet potato demanded the site with comparatively higher temperature for root formation. 25–28 °C led to rapid growth of stem and leaf. When the temperature reached more than 30 °C, the tuber expansion slows down. The temperature of 22–24 °C was conducive to the formation of tuber. Strong light was welcomed for sweet potato; thus the sunny side were selected. Tillage management could also be considered on the basis of

farmer's scale vegetation allocation. For example, straw mulching would enhance soil water storage capacity and lead to reducing the non-point source pollution load through chemical substances intercept. The blueprint on the overall situation would have its full effect combined with some tillage management methods.

To sum up, the development goal for Miyun district is to ensure its position of ecological conservation zone for the whole capital area. The first focus is on the protection of water resources and ecological environment. On the other hand, basic farmland scale protection strategy is made to guide the development of modern urban agriculture actively. For economic improvement, the construction land has completed big achievement. And for sustainable development, overall coordination of urban and rural is about to be set on the population distribution, industrial distribution and land use layout coordination. The government needs to ensure the education work to the public after the land use plan approval. So that leaders of all levels of government, enterprise groups and people from all walks of life will fully understand the importance and authority of land use planning. Improving the awareness of the whole society in accordance with the law is significant to guarantee the smooth implementation process of the land use planning. Dynamic monitoring and management of planning implementation requires to be strengthened by the use of remote sensing, land surveys and other technical means. Scientific support and public anticipation will help the reasonable land use planning towards bright future.

#### 4. Conclusion

This research conducted the optimal land use allocation in Miyun

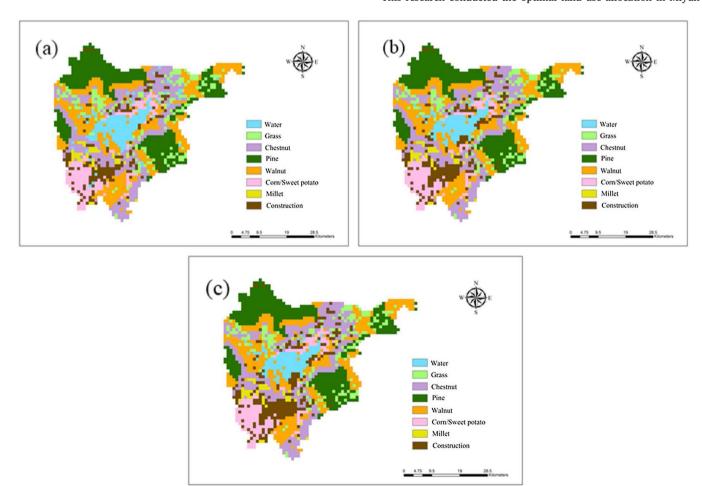


Fig. 15. The spatial distribution for detailed vegetation of the three scenarios ((a) the optimization scenario; (b) the adjustment planning scenario; (c) the government planning scenario for 2020).

District. In order to get more accurate land use type demand, distributed hydrological model was applied to search the regression relations between land use types and runoff changes. R<sup>2</sup> of daily runoff simulation value and measured value was 0.89 while NS was 0.75. The model had good fitting effect which could be applied in the hydrological process simulation. Considering the TN and TP concentrations in overland flow and water use efficiency of different vegetation, the optimal land use demand was determined through multi linear programming.

CLUE-S model was suitable for the land use driving analysis from Miyun District scale. And it could distribute the land use types according to the driving force. The model calibration showed relatively high correspondence. Based on multi linear programming results, three land use scenarios applied in this research. The most optimal scenario pattern, the pattern after the check point year 2010 and the government planning were clearly compared from the land occupation and the distribution aspects. From farmers' perspective, more detailed vegetation configuration was mapped according to the best growth condition for crops. Farmers could get precise guidance by the raster calculation.

The combination of CLUE-S model and MIKE-SHE model improved the accuracy of land use demand and specific vegetation distribution. This analysis conducted comprehensive land use allocation process considering both ecological water saving and pollution control and that would supply scientific support to government decision makers as well as local farmers. The "top-down" land use optimal allocation would support decision makers with feasible suggestions of optimizing land management at different scales. Therefore, this research has carried on certain innovation in theory and technology. In practice, the comprehensive land use allocation of upstream Miyun Reservoir basin provided scientific support for government policy makers and local farmers, as well as improved the scientific and effective administrative management. How to expand the use of range to municipal level, provincial level or even national level would be a key point for researchers. As for the farmers' best cultivation choice, more field monitoring needed to be done for information. Assisted by the combined land use model and hydrological model, land use planning would lead to a more effective way.

#### Acknowledgement

This research was financially supported by the National Natural Science Foundation of China (Grant No. 51421065, 51439001, 51679008), and Chinese National key research and development program (Grant No. 2016YFC0401302).

#### References

- Bryan, B.A., Crossman, N.D., King, D., Meyer, W.S., 2011. Landscape futures analysis: assessing the impacts of environmental targets under alternative spatial policy options and future scenarios. Environ. Model. Softw. 26, 83–91.
- Cai, Y.P., Huang, G.H., Tan, Q., Chen, B., 2011. Identification of optimal strategies for improving eco-resilience to floods inecologically vulnerable regions of a wetland. Ecol. Model. 222, 360–369.
- Chen, L.D., Fu, B.J., 2000. Basic policy framework for sustainable development in Yangtze

- river basin. Resour. Environ. Yangtze Basin 9 (2), 148-153.
- Gastelum, J.R., Valdes, J.B., Stewart, S.A., 2010. System dynamics model to evaluate temporary water transfers in the mexican conchos basin. Water Resour. Manage. 24, 1285–1311.
- Geng, H., Wang, Z.M., 2000. Research on optimization of land use structure based on Gray Linear Programming. J. Wuhan Tech. Univ. Surv. Mapp. 25 (2), 167–171 182.
- Geng, R.Z., Wang, S.Y., Pang, S.J., Yin, P.H., 2016. Identification of key factors and zonation for nonpoint source pollution control in Chaohe River watershed. China Environ. Sci. 36 (4), 1258–1267.
- Hao, Y., 2016. Study on Water Use Mechanism and Its Sable Isotope of Typical Tree Species in Beijing Mountainous Area. Master thesis, Beijing Forestry University.
- Jiao, J., Du, P.F., Lang, C., 2015. Nutrient concentrations and fluxes in the upper catchment of the Miyun Reservoir, China, and potential nutrient reduction strategies. Environ. Monit. Assess. 187 (3).
- Li, Z.J., Li, X.B., 2008. Impacts of precipitation changes and human activities on annual runoff of Chao River Basin during past 45 years. Scientia Geographica Sinica 28 (6), 809–813.
- Li, R.Z., Qian, J.Z., Wang, J.Q., 2003. Study on distribution of total amount of drainage water pollutant in a region. J. Hydraul. Eng. 5, 112–115.
- Li, D.Q., Liang, J., Di, Y.M., Gong, H.L., Guo, X.Y., 2016. The spatial-temporal variations of water quality in controlling points of the main rivers flowing into the Miyun Reservoir from 1991 to 2011. Environ. Monit. Assess. 188 (1).
- Liu, M., Li, C.L., Hu, Y.M., Sun, F.Y., Xu, Y.Y., Chen, T., 2014. Combining CLUE-S and SWAT models to forecast land use change and non-point source pollution impact at a watershed scale in Liaoning Province, China. Chin. Geogr. Sci. 24 (5), 540–550.
- Liu, Y.L., 2003. Land Information System 179 China Agriculture Press, Wuhan.
- Mitsova, D., Shuster, W., Wang, X.H., 2011. A cellular automata model of land cover changes to integrate urban growth with open space conservation. Landscape Urban Plann. 99, 141–153.
- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.
- Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models: part 1. A discussion of principles. J. Hydrol. 10 (3), 282–290.
- Osgathorpe, L.M., Park, K., Goulson, D., Acs, S., Hanley, N., 2011. The trade-off between agriculture and biodiversity in marginal areas: can crofting and bumblebee conservation be reconciled? Ecol. Econ. 70, 1162–1169.
- Ou, Y., Wang, X.Y., Wang, L.X., Rousseau, A.N., 2016. Landscape influences on water quality in riparian buffer zone of drinking water source area, Northern China. Environm. Earth Sci. 75 (2).
- Pontius, R.G., Schneider, L.C., 2001. Land-cover change model validation by an ROC method for the Ipswich watershed Massachusetts, USA. Agric. Ecosyst. Environ. 85 (1–3), 239–248.
- Santini, M., Valentini, R., 2011. Predicting hot-spots of land use changes in Italy by ensemble forecasting. Reg. Environ. Change 11, 483–502.
- Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., Mastura, S.S.A., 2002. Modeling the spatial dynamics of regional land use: the CLUE-S model. Environ. Manage. 30 (3), 391–405.
- Wu, X.N., Jiang, Y., 2010. The impact of climatic change on runoff in Chaohe River Basin. China Rural Water Conservancy Hydropower 2, 5–7.
- Xu, S.J., Wei, S.Q., Xie, D.T., 2004. Analysis of non-point source pollution influence factors and their discrepancy. Resour. Environm. Yangtze Basin 13 (4), 390–393.
- Xu, E.Q., Zhang, H.Q., Dong, G.L., Kang, L., Zhen, X.J., 2016. Spatial variation of water quality in upper catchment of Miyun Reservoir. Water Sci. Technol.-Water Supply 16 (3), 817–827.
- Zhang, P., Liu, Y.H., Pan, Y., Yu, Z.R., 2011. Land use pattern optimization based on CLUE-S and SWAT models for agricultural non-point source pollution control. Math. Comput. Model. 154, 1–8.
- Zhang, G., Guhathakurta, S., Lee, S., Moore, A., Yan, L.J., 2014. Grid-based land-use composition and configuration optimization for watershed storm water management. Water Resour. Manage. 28 (10), 2867–2883.
- Zhang, L., Nan, Z.T., Yu, W.J., Ge, Y.C., 2015. Modeling land-use and land-cover change and hydrological responses under consistent climate change scenarios in the Heihe River Basin, China. Water Resour. Manage. 29 (13), 4701–4717.
- Zheng, J.K., Sun, G., Li, W.H., Yu, X.X., Zhang, C., Gong, Y.B., Tu, L.H., 2016. Impacts of land use change and climate variations on annual inflow into the Miyun Reservoir, Beijing, China. Hydrol. Earth Syst. Sci. 20 (4), 1561–1572.